A review of ten years of implementation and research in aligning learning design with learning analytics at the Open University UK

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Abstract. There is an increased recognition that learning design drives both student learning experience and quality enhancements of teaching and learning. The Open University UK (OU) has been one of few institutions that have explicitly and systematically captured the designs for learning at a large scale. By applying advanced analytical techniques on large and fine-grained datasets, the OU has been unpacking the complexity of instructional practices, as well as providing conceptual and empirical evidence of how learning design influences student behaviour, satisfaction, and performance. This study discusses the implementation of learning design at the OU in the last ten years, and critically reviews empirical evidence from eight recent large-scale studies that have linked learning design with learning analytics. Four future research themes are identified to support future adoptions of learning design approaches.

Keywords: Learning Design, Learning Analytics, Engagement, Satisfaction, Performance.

1 Introduction

The past decade has seen a growing body of literature [1-4] that seeks to develop a descriptive framework of instructional practices so that effective teaching approaches can be shared between educators and reused. Several educational initiatives have been undertaken to gain better insights how teachers design and implement face-to-face, blended and online courses, and what works. These initiatives have focused on what has been called design for learning or learning design, and include among others the Educational Modelling Language project (EML) [5], the SoURCE project [6], the Australian Universities Teaching Council (AUTC) LD project [7], the Learning Activity Management System (LAMS) [8], LdShake [9], and the Open University Learning Design Initiative [10].

Learning Design (LD) [11], the approach developed and used by the Open University (OU), is described as “a methodology for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions, which is pedagogically informed and makes effective use of appropriate resources and technologies” [1]. In other words, LD is focused on ‘what students do’ as part of their learning, rather than on 'what teachers do' or on what will be taught. Within the OU, there is an increased recognition that LD is an essential driver for learning [12-18].

Recent technological developments have allowed researchers and practitioners alike to capture the digital traces of learning activities of students and teachers in Virtual Learning Environments (VLEs). This rich and fine-grained data about actual learner behaviours offer educators potentially valuable insights into how students react to different LDs. However, despite substantial progress in transferring LD from implicit to explicit, there remains a paucity of evidence for how learners respond to different LDs.

The unprecedented increase in education data that VLEs have made available over recent years has also given birth to the field of learning analytics (LA). LA is defined as " the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [19]. A considerable literature has emerged around both conceptual development [19,20] and how to design appropriate predictive learning analytics to support students [21,22]. One of the main challenges for LA research is to deliver actionable feedback, which might be achieved by taking into account the context in which the learning data is situated [21,23]. Thus, there is an increasing interest to align LA with LD, as the former facilitates making tacit educational practice explicit, while the latter provides educators with pedagogical context for interpreting and translating LA findings for direct intervention [24-28].

Although we acknowledge that substantial progress has been made at various institutions how LD can help to inform teachers and learners [29-31], few institutions have implemented LD on such a large scale as the Open University UK (OU). Furthermore, few institutions, again with the notable exception of the OU, have captured and combined these data with behavioural traces of students in order to reflect on how these modules are delivered to students [32]. While a large number of researchers have made conceptual claims that LD is an essential driver for student learning [1,29,31,27], there is limited empirical evidence to support this claim. Therefore, after ten years of developing, testing, implementing and evaluating the evolving large-scale practice of LD at the OU, in this review we aim to critically assess the following main research question: To what extent is there robust empirical evidence of the impact of learning design on educational practice and how students learn? In order to address this main research question, in this contribution to the special issue we will first discuss how the OU implements LD, and in particular how we map our modules. Second, we will compare, contrast and review eight large-scale studies at the OU that have linked LD with LA. Finally, based upon our practical experiences and research insights, we will propose four large research questions that might inspire researchers, practitioners and institutions to enhance our understanding of LD.

2 Learning Design at the OU

At the beginning of the 21st Century, several researchers at the OU started to focus on conceptually mapping and understanding how teachers were making decisions about what and how to teach at a distance. For example, Conole et al. [33] started experimenting with mapping learning design processes, whereby they "developed an approach to using learning design as a methodology to guide design and foster creativity in concert with good practice in the creation of learning activities".

Table 1. Learning design (LD) activities

LD activity	Details	Example
Assimilative	Attending to information	Read, Watch, Listen, Think about, Access.
Finding and handling information	Searching for and processing information	List, Analyse, Collate, Plot, Find, Discover, Access, Use, Gather.
Communication	Discussing module related content with at least one other person (student or tutor)	Communicate, Debate, Discuss, Argue, Share, Report, Collaborate, Present, Describe.
Productive	Actively constructing an artefact	Create, Build, Make, Design, Construct, Contribute, Complete,
Experiential	Applying learning in a real-world setting	Practice, Apply, Mimic, Experience, Explore, Investigate,
Interactive/adaptive	Applying learning in a simulated setting	Explore, Experiment, Trial, Improve, Model, Simulate.
Assessment	All forms of assessment (summative, formative and self-assessment)	Write, Present, Report, Demonstrate, Critique.

Source: http://www.open.ac.uk/iet/learning-design/sites/www.open.ac.uk.iet.learning-design/files/files/ecms/web-content/Downloads/102-activity-planner.pdf

Building on this initial work, the OU's LD taxonomy was established as a result of the Jisc-sponsored OU Learning Design Initiative (OULDI) [10], and was developed over five years in consultation with eight other Higher Education institutions. In contrast to instructional design, LD is process based [1]: following a collaborative design approach in which OU module teams, curriculum managers and other stakeholders make informed design decisions with a pedagogical focus, by using representations in order to build a shared vision. The OU categorises LD in terms of seven broad *LD activities* (see Table 1).

Assimilative activities are tasks in which learners attend to discipline-specific information. This includes reading text (online or offline), watching videos, or listening to an audio file. *Finding and handling information* activities (which might involve information sources such as the Internet or spreadsheets) are those which focus on skills development and encourage learners to take more responsibility for their learning. *Communicative activities* are those in which students communicate with another person about module content. *Productive activities* are those in which learners build and co-construct new artefacts. This could be a list, a piece of narrative text which answers a question, a reflective account, a report, a video or a presentation. *Experiential activities* provide learners with the opportunity to apply their learning to a real-life setting. The key here is that students receive real-life feedback on the activity (for example, from customers or clients, work colleagues or the environment) and have an opportunity to reflect in context. *Interactive / adaptive activities* do a similar thing but in a pedagogically or practically safe setting, such as those provided by simulations. Activities falling into this category might include role-play, problem-based scenarios, simulated case studies or simulated experiments. Finally, *assessment activities* encompass all activities focused on assessment, whether formative (to monitor and feedback on progress, peer review or self-assessment) or summative (for measurement and qualifications).

For the development, review or redesign of modules, the OU uses a process of so-called "module mapping". Beginning with a stakeholders' workshop, in which the various possible LD activities are discussed in the context of the module being designed, the module's initially intended LD is analysed and subsequently presented back to the module team as a combination of graphics and text (by means of the OU's Activity Planner visualisation tool). The aim is to make explicit the module teams' otherwise tacit LD decisions so that they might consider whether amendments to their LD might enhance the quality of their module. Around 300 modules have thus far been mapped at the OU.

The mapping process is comprehensive, but labour-intensive – typically taking between three and five days for a single module, depending on the module's number of credits, its structure, and quantity of learning resources. A team of LD specialists within the Institute of Educational Technology (IET), which is part of the OU's Learning, Teaching and Innovation portfolio (LTI), reviews all the available learning materials, classifies the types of activity, and quantifies the time that students are expected to spend on each activity (as illustrated in Figure 1).

As indicated by Rienties and Toetenel [12], classifying learner activity can be subjective but consistency is important when comparing module designs across disciplines in the institution. Therefore, the Learning Design team holds regular meetings, involving LD team members and module team members, to improve the consistency. The meetings enable a form of moderation (informal 'inter-rater reliability') to take place. For example, LD team members map the same week of a specific module, following which they share their findings, differences are discussed and a common approach is agreed. Finally, the Learning Design team manager reviews the module and its LD. In other words, each mapping is commonly reviewed by at least three people. This shared understanding leads to greater consistency of approach, and enhances the reliability and robustness of the data. It also feeds into guidance and support provided by the Learning Design team for faculty staff (e.g., via regular training courses for curriculum managers), to build their skills and confidence in the mapping process. Increasingly, following the training, faculty-based module teams are also mapping the modules themselves in order to compare initial and implemented LD and also to facilitate further iterative development during module production or review.

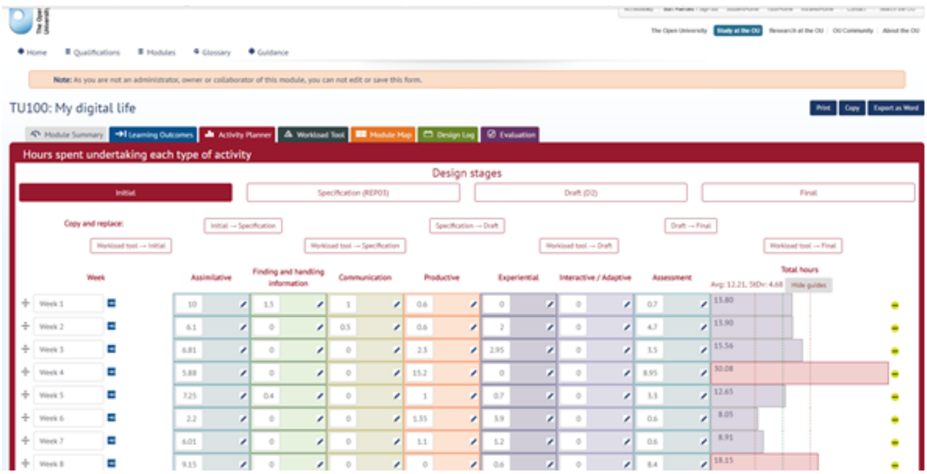

Fig. 1. Module activities within a level 1 module (overview of first 8 weeks)

In addition, an estimation is made for how long it would take an average student to complete each activity (per week). Inevitably, in practice it might be that some activities (e.g., watching a 5 minute video with questions afterwards, reading 500 words on a Shakespeare play, finding out why global warming in Costa Rica has accelerated in the last five years) might take longer for some students than others. Nonetheless, an online tool, the OU Learning Design workload tool, is used to capture this data automatically on a week-by-week basis, with agreed conventions for study speed and amount of time allocated to studying figures, tables, images, audio and video within module materials. Study speed can be set at low, medium or high, depending on the type of material, the level of study, or other influencing factors such as concept density. Study speed assumes that as well as reading the text, students will take additional time to absorb and reflect on what they read. In principle, each module mapping can be updated by module teams every presentation (every time the module is made available to a new cohort of students). Module teams can transfer data from the Learning Design workload tool back into the Activity Planner visualization tool, in which they can adjust the module activity timings as needed.

3 Learning Analytics at the OU

As highlighted by OU research, LA could provide explicit feedback on LD based on actual learner responses through trace data [27,24,26,11]. Traditionally, learner responses have often taken forms of evaluation surveys, assessments, and feedback through behavioural cues or verbal comments [34-37]. In an interview based study of 30 educators, Bennett et al. [38] reported that educators continuously seek for feedback on their LD through student comments and reactions. Although these established feedback channels have been adopted by educators for a long time, they are rather limited to capture how students response to LDs in real-time and on a large scale. For instance, evaluation surveys are usually regarded by many institutions as a reference point to improve their instructional practice [34-37]. However, these channels may suffer from selection bias, response bias, and only take place once the learning process has finished (at the end of a course). Indeed, a recent meta-analyses of 51 articles consisting 97 multisection studies by Uttl et al. [39] found no correlations between student evaluations of teaching and actual learning performance. Thus, these data sources may leave not much room for direct interventions while a module is in presentation. As argued by Rogaten et al. [40], formative assessments and summative assessments could be potentially strong measures of effectiveness of LD, but these assessment measure the "product of learning" rather than how learners respond to the design for learning. Picking up behavioural cues and verbal comments through interaction with students could offer a rich resource of feedback to educators. However, they might not be applicable to a large scale study context, or in a VLE.

One advantage of LA is the capability to capture and analyse fine-grained data of learners, such as the time spent on a particular activity, and the frequency of visits. Combining trace data with demographics and performance history allows educators to both make personalised interventions to each student as well as to adjust the course according to the overall trends of a group of students. Persico, Pozzi [26] argued that pre-existing aggregated data on students' engagement, progression, and achievement should be taken into account in designing learning activities in combination with prior teaching experience, or best practice of colleagues. In a similar manner, Mor et al. [27] suggested that LA could facilitate teacher inquiry by transforming knowledge from tacit to explicit, and perceive students and teachers as participants of a reflective practice.

4 Linking Learning Design with Learning Analytics

Although meaningful patterns and trends generated from VLE data have been uncovered using various analytical techniques, the main challenge faced by LA researchers is to establish a connection between LA and pedagogy [41-43]. Without a pedagogically-sound approach, researchers might have a difficult time identifying what to measure, which variables should be investigated, and how to translate LA findings to direct interventions [43]. For example, a recent large-scale study reviewing the use of predictive analytics tools called OU Analyse with 240 teachers in 10 modules at the

OU revealed that while teachers expressed interest in using predictive learning analytics data in the future to better support students at risk, there has not been a clear benefit between groups of teachers having access to OU Analyse and groups of teachers with no access [44]. Hence, LD could potentially equip researchers with a narrative behind their numbers, and convert trends of data into meaningful understandings and opportunities to make sensible interventions.

There have been numerous studies that proposed a conceptual link between LA and LD. For example, Lockyer et al. [24] suggested two categories of analytics applications: checkpoint analytics to determine whether students have met the prerequisites for learning by assessing relevant learning resources, and process analytics to capture how learners are carrying out their tasks. Another study by Persico, Pozzi [26] argued three dimensions of LD that can be informed by LA: representations, tools, and approaches. Recently, Bakharia et al. [28] proposed four types of analytics (temporal, tool specific, cohort, and comparative), and contingency and intervention support tools with the teacher playing a central role.

To sum up, research in both fields have highlighted the mutual benefits of connecting LA and LD. Although these studies provide some important stepping stones for future empirical research, to the best of our knowledge no study outside the OU has linked learning designs with learning analytics for a large number of modules and disciplines. In the following section, several lines of evidence on how LA informed LD will be reviewed at the OU.

5 Empirical evidence of impact of LD on OU educational practice

In the first six years of developing and implementing LD at the OU mostly qualitative techniques and conceptual approaches [1,33,10] were used to understand and unpack how teachers were adopting OULDI. With the increased interest in big data and the establishment of a learning analytics research programme in 2013 within the Institute of Educational Technology at the OU, a gradual shift in conceptualisation and advanced quantitative and mixed-method research approaches has taken place. This is evidenced by eight empirical articles that have been produced by the OU that have linked LD and LA (Table 2). Note that these studies are presented based upon their respective (online) publication date, which necessarily does not automatically show our non-linear, evolving conceptualisations of LD and LA. Below we provide a short summary of each article, some of which have already been briefly mentioned, and how these findings can be used to support design of modules and qualifications. Subsequently, in order to address our main research question we will critically revisit some of the studies that we have already mentioned to consider them in more detail.

Table 2. Eight empirical studies linking learning analytics with learning design at the OU

Study	Aims	Methods
1. Rienties et al. [13]	How learning designs affect VLE behaviour and performance	Cluster- and correlation analyses on 87 modules
2. Rienties, Toetenel [12]	How learning designs affect VLE behaviour, satisfaction, and performance	Multiple regression models on 151 modules
3. Toetenel, Rienties [14]	How learning designs were configured and its effects on performance	Visualization and correlation analyses of 157 modules
4. Toetenel, Rienties [45]	Whether the combination of a collaborative, networked approach at the initial design stage, augmented with visualizations, has changed the way educators design their courses	Comparison of 148 learning designs prior and post Learning Design Initiative
5. Nguyen et al. [17]	How learning designs were configured longitudinally across modules and its effects on VLE behaviour	Visualization, network analysis, and fixed-effect regression model of 38 modules over 30 weeks
6. Nguyen et al. [16]	How learning designs of computer-based assessment were configured and its effect on VLE behaviour, satisfaction, and performance	Visualization, mixed-method of fixed-effect regression models and a descriptive framework of 74 modules.
7. Nguyen et al. [46]	How learning designs were configured at activities level and the media used to deliver.	Visualization, and network analysis of 1 module and its 268 learning activities
8. Rienties et al. [18]	Mixed method analyses how learning design approach might need to be adjusted to disciplinary context	Visualization, mixed-method of fixed-effect regression models and a fine-grained framework of 4 language modules.

In our first large-scale empirical study linking learning design and learning analytics at the OU, Rienties et al. [13] used K-means cluster analysis on 87 modules to identify four common patterns of learning activities of how OU teachers developed distance learning modules. Perhaps surprisingly given the strong standardisation processes at the OU, we found four relatively distinct clusters of learning design: constructivist, assessment-driven, balanced-variety, and social constructivist (Figure 2). Cluster 1 (constructivist) emphasized strongly on assimilative activities such as reading, watching, and listening. Cluster 2 (assessment-driven) allocated a fair amount of time for assessment (both formative and summative) while had limited focus on assimilative, communication, and interactive activities. Cluster 3 (balanced-variety) illustrated a relatively more balanced design between seven types of learning activities with a relatively high focus on experiential activities. Finally, cluster 4 (social-constructivist) used more a learner-centred learning design approach, whereby relatively more time was devoted towards communication, productive and interactive activities.

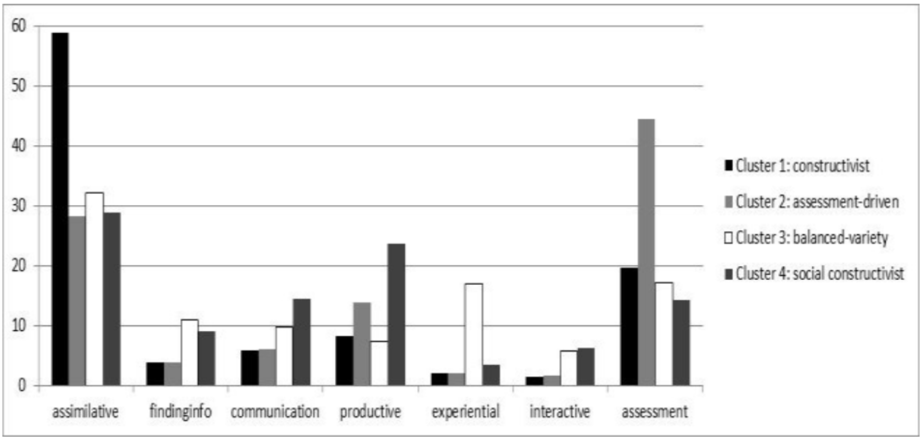

Fig. 2. Cluster analysis of learning design (Retrieved from Rienties et al. [13])

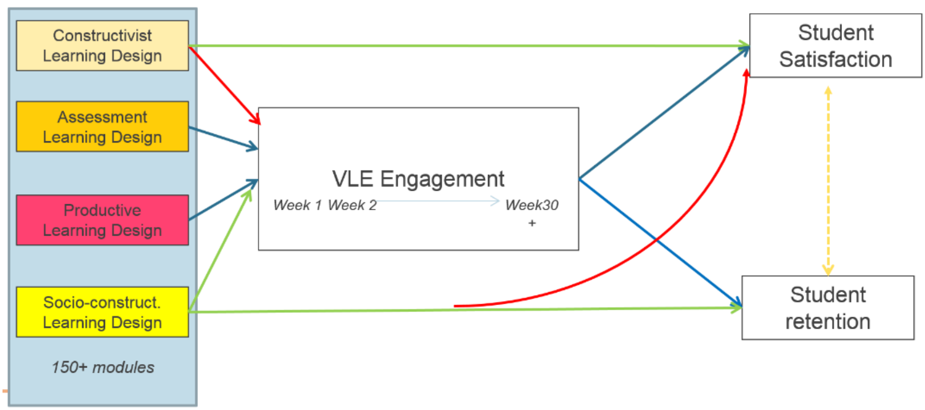

Fig. 3. Learning design strongly influences student behaviour, satisfaction and performance (Adjusted from Rienties, Toetenel [12])

In follow-up research, Rienties, Toetenel [12] linked 151 modules taught in 2012-2015 at the OU followed by 111,256 students with students' behaviour using multiple regression models and found that learning designs strongly predicted VLE behaviour and performance of students, as illustrated in Figure 3. Findings indicated that the primary predictor of academic retention was the relative amount of communication activities. This may be an important finding as in particular in online learning there tends to be a focus on designing for individual cognition rather than social learning activities [47,30], while recently several researchers have encouraged teachers and researchers to focus on the social elements of learning [48,47].

A second important finding was that learner satisfaction was strongly influenced by learning design [12]. Modules with assimilative activities and fewer student-centred approaches like finding information activities (i.e., constructivist learning designs) received significantly higher evaluation scores. However, a crucial word of caution is in place here. Although we agree with others [47,49,50] that learner satisfaction and happiness of students is important, it is remarkable that learner satisfaction and academic retention were not even mildly related to each other in Figure 3, as also evidenced by the recent meta-review of [39] . Given that students who complete a student evaluation questionnaire are a sub-set of the entire cohort of students, and students who drop out at the beginning of the module are less likely to complete a student evaluation questionnaire, one has to be careful in interpreting these findings. More importantly, the (student-centred) learning design activities that had a negative effect on learner experience had a neutral to even positive effect on academic retention. The primary predictor for retention was communication, so when designing modules OU staff will have to strike a delicate balance between "happy" students and retention.

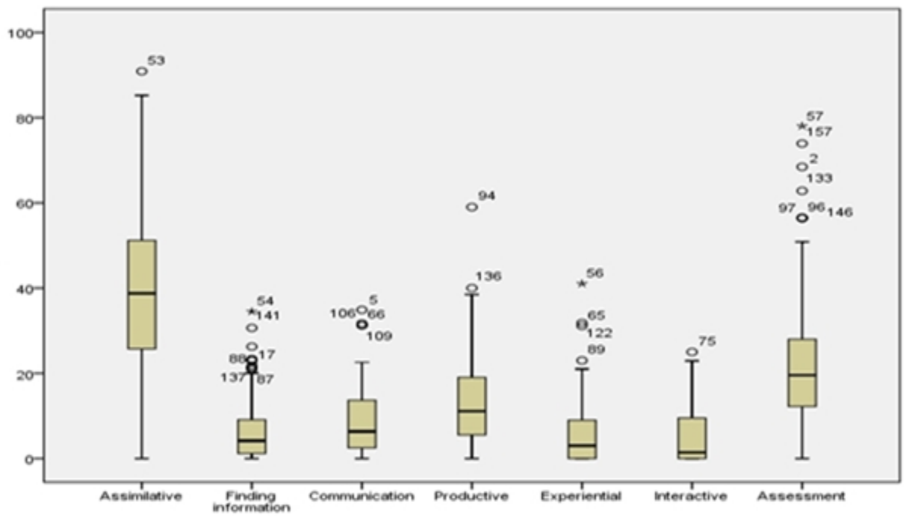

Fig. 4. Boxplot of seven learning design activities of 157 courses (in percentages) (Retrieved from Toetenel, Rienties [14])

In our third large-scale empirical OU study comparing 157 learning designs at the OU, Toetenel, Rienties [14] found that on average students were expected to spend 21.50% of their study on assessment, although substantial variation (SD = 14.58%, range 0-78%) was found amongst these modules when comparing 157 modules at the OU. As highlighted in Figure 4, a vast range of designs were present at the OU, but most of them used a relatively high focus on assimilative and assessment learning activities, with relatively lower usage of more student-active activities (e.g., finding information, communication, productive).

In the fourth OU empirical study of 148 learning designs by Toetenel, Rienties [51], the introduction of a systematic learning design initiative consisting of visualization of initial LDs and workshops helped educators to focus on the development of a range of skills and more balanced LDs. As illustrated in Figure 5, when OU members of staff were given visualisations of their initial learning design activities (i.e., orange) compared to teachers who were not given these visualisation (i.e., blue), they adjusted their designs towards more student-active activities, such as communication and finding information, while reducing the emphasis on assimilative.

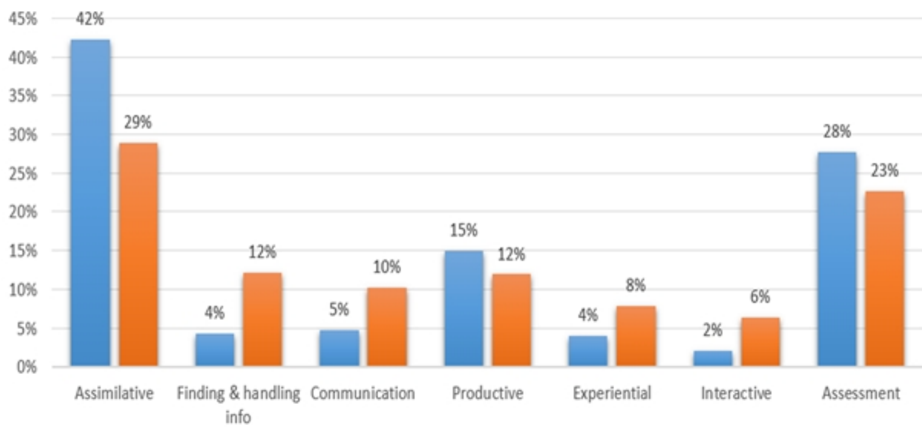

Fig. 5. Changing learning design of OU teachers (before and after visualisations) (Retrieved from Toetenel, Rienties [45])

While the previous four studies explored LD from a static perspective, in the two last years, more fine-grained weekly LD data has been added, which allowed us to potentially identify the optimum mix of LD activities per discipline, level, and type of students per week and over time. The fifth OU empirical study by Nguyen et al. [16] on learning designs of 74 modules over 30 weeks with a focus on Computer-Based Assessment (CBA) revealed that the workload on a weekly basis on other activities decreased when assessment activities were introduced (as illustrated in Figure 6). This implied that educators at the OU aimed to balance the total workload when designing CBA. Secondly, our fixed effect models indicated that assessment and communication activities significantly predicted the time spent on VLE. Overall, by controlling for heterogeneity within and between modules, learning designs could explain 69% of the variance in VLE behaviours. Furthermore, assessment activities were significantly related to pass rates, but no clear relation with satisfaction was found.

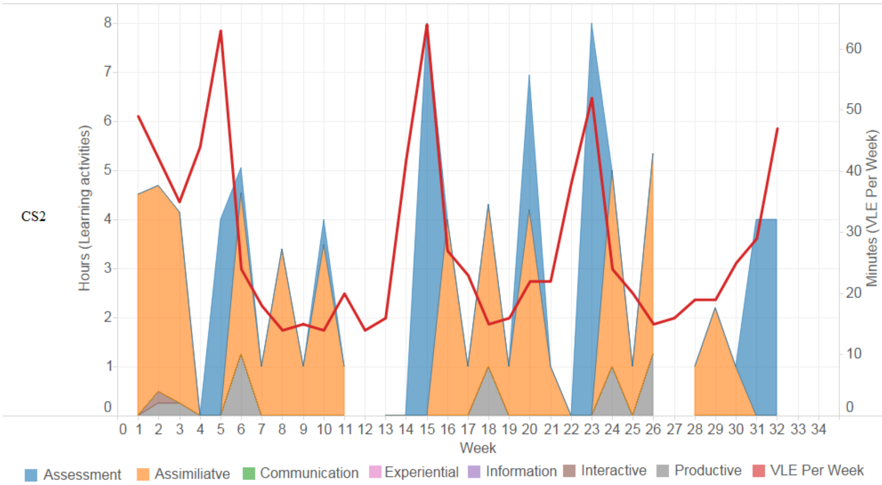

Fig. 6. Longitudinal visualisation of learning design (coloured blocks) and average student engagement (red line) in the VLE each week for CS2 (Retrieved from Nguyen et al. [16])

In the sixth OU empirical study by Nguyen et al. [17], we took a further step to unpack the complexity of learning design by applying network analysis techniques to investigate the inter-relationships among different types of learning activities (Figure 7). Our findings suggested that learning designs varied considerably across different disciplines. For example, module 1 in Art and Social Sciences often used a combination of assimilative and productive activities, or assimilative and finding information activities. Module 2 in Business and Law had more balanced connections between different learning activities. Module 3 in Languages and Education only combined only three types of learning activities together. Our network analysis suggested that if we only concentrate on a single component of learning design in isolation, we might omit the complexity and critical features of the instructional dynamic, see again Figure 7.

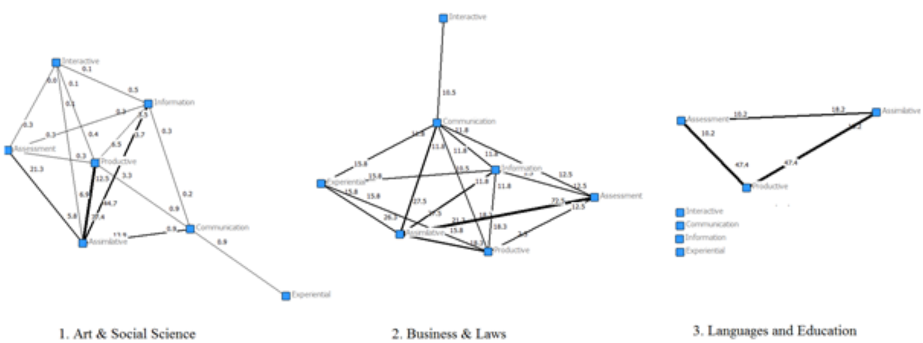

Fig. 7. Learning design activities per module (Retrieved from Nguyen et al. [17])

In our follow-up seventh OU study on 268 individual learning activities of a module over 30 weeks, Nguyen et al. [46] demonstrated that the interlinkage between the media used to deliver assimilative activities and its inter-relationships with other learning activities (Figure 8). In general, most assimilative activities took forms of words, which suggests that educators were more likely to use reading materials to convey information, but also included another media elements. Further network analysis revealed strong ties between words, figures, photos, and tables. This implies that educators employed an integrated representations of words and graphics, which has been shown to be effective in helping learners absorb information.

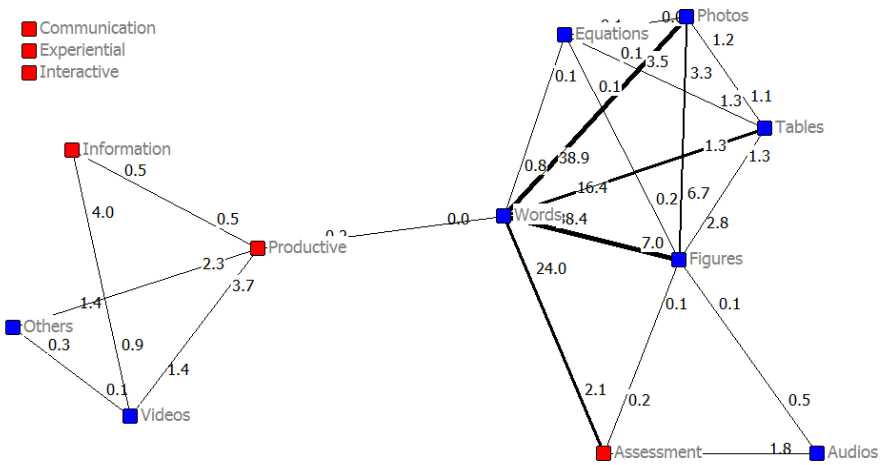

Fig. 8. Inter-relationships between assimilative activities and other activities of an exemplar module in Social sciences (Retrieved from Nguyen et al. [46])
Note: Blue nodes represent assimilative activities, red nodes represent other activities

Finally, our most recent and eighth OU study used fine-grained data of four language studies, whereby Rienties et al. [18] contrasted weekly learning design data of 2111 learners. The findings indicated that the OULDI taxonomy needed to be slightly adjusted for the language context, as communication activities were labelled differently in this specific discipline. As exemplified by these mapping data, one of the potential risks of applying an institution wide OULDI taxonomy is that its application varies widely across disciplines. Our qualitative analyses indicated that language teaching used very specific meta-language for instruction, such as receptive skills, or authentic assessment. This subject specific meta-language was not present in the original taxonomy so the Learning Design team in collaboration with the Language Faculty developed a translation for each activity to better reflect the four macro-skills of reading, writing, speaking and listening. Nonetheless, using fixed effect models, our findings indicated that 55% of variance of weekly online engagement in these four modules was explained by the way language teachers designed weekly learning design activities.

6 Conclusions and Future Research

In this review of 10 years of learning design research at the Open University UK, we have reflected on how the conceptual development of learning design and the OULDI approach in particular. The LD design approach developed at the OU has led to both large-scale uptake by academics and instructional designers as well as a recent surge of a number of large empirical studies to test how well learning design activities actually match reality (i.e., students' behaviour and learning outcomes). While most studies on learning design focus primarily on conceptual development of different learning design taxonomies [24,26,28], the OU is proactively testing and evaluating how the OULDI taxonomy works in practice amongst hundreds of modules, and how we can optimise the learning from our students. Given that the OU is slightly ahead in terms of empirically linking large learning design datasets with learning analytics data, we hope that by sharing our research findings and future research strands we will inspire others to join us on our journey to advance robust and high-quality learning design research.

In terms of our main research question, as highlighted from our earlier work [13,45,12,14], learning design decisions made by OU teachers seem to have a direct and indirect impact on how students are working online and offline, which in part also influenced their satisfaction and learning outcomes. Particularly promising is the research by Toetenel, Rienties [45], who showed that visualising initial learning design decisions to teachers significantly impacted their final mix of learning design activities. Follow-up analyses indicated that by discussing initial learning design activities in workshops, sharing good practice, and visualising initial learning decisions teachers designed fewer assimilative activities, and more student-centred learning activities. This is a very important result for the learning design community, as it highlights that institutions can pro-actively support and train teachers, and where needed encourage them to balance appropriate learning activities that maximise students' potential.

Our more recent work [46,17,16,18] provides important fine-grained detail about how teachers balance learning design activities on a week-by-week basis using advanced statistical models, visualisations, and social network techniques. Our findings highlight that how teachers mix learning design activities substantially impacts what students do on a weekly basis, whereby between 40-69% of variance of VLE engagement is predicted by learning design and its module characteristics. This is far more than we initially expected, given that many modules at the OU still have substantial offline components, and students have some degree of flexibility to decide what and when to study. At the same time, our fine-grained and advanced analyses indicate substantial misalignments of how teachers design modules, in particular when comparing the learning designs within a discipline or qualification. This misalignment between learning designs in consecutive modules might hamper students' progression over time, as students may need to adjust their learning strategies for each new module, which may lead to transitional problems.

6.1 Moving forwards to advance learning design research

Based upon ten years of learning design research, and a recent surge in large-scale empirical research on learning design, we have identified four large research questions that we aim to address in the near future at the OU. Note that these four future research questions were identified and constructed jointly by the authors and are both a reflection of our own lived experiences at the OU and other institutions, and our own and joined research agendas.

Our first research question aims to validate how reliable the LD codings are for teachers and students, and how they could be further improved. Although substantial amounts of data on expected workloads on the seven learning activities are compiled, specific details about the specific tasks are currently not coded explicitly in the OULDI approach. For example, formative assessment activities, such as interactive computer-marked assessments or peer feedback, are coded in a similar manner to summative assessment activities, such as final exam. There is a wide and diverse body of literature on assessment that has highlighted that learning scientists need to distinguish between formative and summative assessments, as their underlying processes and outcomes are fundamentally different [16,52,53]. Similarly, the type of communication activities (student to student, student to group, student to teacher, collaborative) are aggregated into one activity, while fine-grained data about the types of interactions would help to unpack which learning design activities in terms of communication really help to increase retention. The learning design team is currently working towards more fine-grained recording of activities. Similarly, as highlighted by our most recent study [18] disciplinary contexts might influence how teachers "translate" the OULDI learning design into their own practice. Therefore, our OULDI approach, as any other LD approach, needs to be flexible enough for teachers across the disciplines to use it effectively, while at the same time ensuring that a coherent meta-structure remains in place to advance our insights and learning analytics research into what works across disciplines.

A second question to be explored further is how specifically learning design can improve retention rates by achieving the optimum balance between satisfaction and challenge in learning, so that students are supported to move beyond their comfort zone. This question arises from the rather contradictory findings of study 2 that students seem to prefer traditional distance learning modules, but in fact seem to perform better on socio-constructivist modules in terms of pass rates. Well-designed collaborative learning activities can provide a means of scaffolding student learning, as students share insights and support each other to achieve a task. Although student feedback often suggests that students do not enjoy working together in groups and prefer to study independently, recent OU research has identified a correlation between amount of collaborative activity, and student completion and pass rates (summarised by van Ameijde et al. [54]). In addition, the ability to work effectively as part of a team is a key skill sought by employers; therefore developing collaborative working practices may enhance students' life chances beyond study.

A third question that is thus far only addressed indirectly in most LD research is the students' voice on learning design. Although students are regularly asked for their feedback after studying a module [37], until recently students have had relatively few opportunities to be involved in the design process itself. The OU's Learning & Teaching Innovation curriculum design student panel is currently experimenting with enabling students to contribute to module development and learning design at a much earlier stage, through focus groups and regular small online activities. As a result, knowledge about the student learning experience is being enriched, and can be fed back into the design process along with learning analytics data.

A final question which probably is the most important of all is how specific learning design activities actually relate to fine-grained learning behaviour, while recognising that students are different and unique. While our research [46,17,16,18,12,13] has found that aggregate and weekly learning design data significantly predict students' online engagement, at present we were only able to use aggregate proxies of such engagement (e.g., number of minutes spent online, number of clicks). Of course this is a substantial simplification of what students actually do, and it would be essential to link what students are actually doing, with which level and intensity, with learning design activities. For example, if a teacher has designed a forum activity on "reflecting what your street looks like" as a small 10% activity in week 7, some students may spent 95% of their time in week 7 on commenting on others' posts, while others may spent only 1% of their time on this activity. Aggregating this data obviously leads to a rather simplified reality of how learning design links to online behaviour. One reason why thus far we have not integrated these fine-grained data is the inherent complexities of large log files and complex data structures. In addition, up to recently the OU (like many other institutions) only shared aggregated learning analytics data with specific users, while fine-grained data was recycled given the sheer size of the organisation [55]. Thus, more research is needed to unpack learning behaviour on VLE at activity level as it could help instructors and designers to refine their estimates of learning activities, and optimise the learning design for each unique student.

In conclusion, building on recent insights of learning sciences, if we are able to link fine-grained learning design activities with what students are actually doing, not only can it be tested which educational pedagogies and conceptualisations work best for which types of students, but more importantly we can push the boundaries of formative learning analytics to provide effective support for both teachers and individual learners [56]. We hope that our contribution to this special issue will inspire others to also integrate large scale learning analytics data with learning design, and we are looking forward to collaborating and contrasting our findings with other institutions.

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